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Cyclostationary Algorithm for Signal Analysis in Cognitive 4G Networks with Spectral Sensing and Resource Allocation

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Article History	***Abstract***
Received: 18 July 2022 Revised: 26 September 2022 Accepted: 25 October 2022	Cognitive Radio (CR) effectively involved in the management of spectrum to perform improved data transmission. CR system actively engaged in the data sensing, learning and dynamic adjustment of radio spectrum parameters with management of unused spectrum in the signal. The spectrum sensing is indispensable in the CR for the management of Primary Users (PUs) and Secondary users (SUs) without any interference. Spectrum sensing is considered as the effective adaptive signal processing model to evaluate the computational complexity model for the signal transmission through Matched filtering, Waveform and Cyclostationary based Energy sensing model. Cyclostationary based model is effective for the energy based sensing model based on unique characteristics with estimation of available channel in the spectrum to extract the received signal in the PU signal. Cyclostationary based model uses the spectrum availability without any periodic property to extract the noise features. This paper developed a Adaptive Cross Score Cyclostationary (ACSCS) to evaluate the spectrum sensing in the CR network. The developed ACSCS model uses the computational complexity with estimation of Signal-to-Interference-and-Noise Ratio (SINR) elimination of cost function. ACSCS model uses the Adaptive Least square Spectral Self-Coherence Restoral (SCORE)

CC License CC-BY-NC-SA 4.0	with the Adaptive Cross Score (ACS) to overcome the issues in CR. With the derived ACSCS algorithm minimizes the computational complexity based on cost function compared with the ACS algorithm. To minimize the computational complexity pipeline triangular array based Gram-Schmidt Orthogonalization (GSO) structure for the optimization of network. The simulation performance analysis with the ACSCS scheme uses the Rician Multipath Fading channel to estimate detection probability to sense the Receiver Operating Characteristics, detection probability and probability of false alarm using Maximum Likelihood (ML) detector. The ACSC model uses the Square-law combining (SLC) with the moment generation function in the multipath fading channel for the channel sensing with reduced computational complexity. The simulation analysis expressed that ACSC scheme achieves the maximal detection probability value of 1. The analysis expressed that proposed ACSC scheme achieves the improved channel estimation in the 4G communication environment. ***Keywords: Cyclostationary algorithm, Signal-to-Interference-and-Noise Ratio, Probability of Detection, Multipath Fading, Gram-Schmidt Orthogonalization (GSO)***

1. Introduction

An improved form of Software Designed Radio (SDR), otherwise called Mental Radio (CR), is an innovation that has as of late seen rising prominence in remote applications. The justification for ongoing interest in this procedure is mostly because of their additional element of dynamic range designation strategy [1]. Worldwide principles utilize CR to successfully use the unused piece of the range for remote interchanges and they are now settled or being lay out by IEEE 802.22 norms. By utilizing CR innovation, it is feasible to detect the climate and change the organization to oblige any change. The vitally mental undertaking expected to accomplish dynamic sharing is alluded as a mental cycle [2]. The three primary strides of this cycle are range detecting, range investigation and range choice. Range detecting is the main fixing among others for sending off the CR in remote gadget. Range detecting not just registers the ghostly substance and obstruction temperature over the range yet in addition decides sort of balance, transporter recurrence and transmission capacity of the Discharge band. In any case, this requires predominant versatile sign examination with extra computational intricacy [3].

Cyclostationarity highlight recognition is a strategy for recognizing PU signal by using the Cyclostationarity elements of the got signals [4]. Cyclostationary highlights, for example, cyclic auto connection capability and ghostly relationship capability are utilized to identify such signals present in a given range. The Cyclostationarity-based identification calculations can separate channel commotion from PU signals, since the channel clamour is Wide-Sense Fixed (WSS) which doesn't have relationship property [5]. PU signals are Cyclostationary with ghostly connection, because of the overt repetitiveness of sign periodicities.

Cyclostationary highlight recognition depends on cyclic connection capability which can powerfully distinguish feeble signs from Discharge by just using the Cyclostationarity property of correspondence signals [6]. Notwithstanding, the high execution intricacy confines its broad use. As of late, a few works have been examined to lessen the computational intricacy of Cyclostationary based range detecting calculation in CR framework through consistent modulus calculation [7] ideal Radiometer, Fourier range cyclic thickness (SCD) [8], multitaper - Loeve rendition [9] and Ghostly Self-Cognizance Restoral (SCORE) [10]. These are the most alluring ones because of good framework execution and low intricacy. Among these strategies, SCORE calculation is the most effective methodology, express, logically manageable assembly and determination properties, which give them a benefit over the other property restoral procedures. One more significant benefit of the

SCORE calculations over customary strategies is that the main fundamental boundary for these calculations is the cycle recurrence of the ideal signs [11].

There are five SCORE based Cyclostationary beamforming new algorithms proposed [12], namely the Adaptive Cyclic Adaptive Beamforming (ACAB), Adaptive Cross-SCORE (ACS), Adaptive Least-Squares (ALS), Adaptive Phase-SCORE (APS), and Maximal Constrained Autocorrelation (MCA) algorithms [13]. In these SCORE based algorithms, the received signals are multiplied by the weighting factor and then they are added together to produce alternative transmit data holding the same information. A matrix inverse lemma formula is applied in all the above algorithms to reduce the computational complexity. Hence, all these algorithms have a far more reasonable implementation complexity than the traditional cyclic-spectrum estimation-based Cyclostationary feature detectors [14]. Each of these algorithms has the specific application. Among these five algorithms, ACS can turn out high performance for well-built interference and can produce good results in the case of average or fragile interference.

In this paper, it proposed an Adaptive Cross Score Cyclostationary (ACSCS) for the spectrum and channel estimation in the 4G wireless communication. The ACSCS scheme uses the Signal-to-Interference-and-Noise Ratio (SINR) elimination of cost function. ACSCS model uses the Adaptive Least square Spectral Self-Coherence Restoral (SCORE) with the Adaptive Cross Score (ACS) to overcome the issues in CR. With the derived ACSCS algorithm minimizes the computational complexity based on cost function compared with the ACS algorithm. To minimize the computational complexity pipeline triangular array based Gram-Schmidt Orthogonalization (GSO) structure for the optimization of network. The simulation performance analysis with the ACSCS scheme uses the Rician Multipath Fading channel to estimate detection probability to sense the Receiver Operating Characteristics, detection probability and probability of false alarm using Maximum Likelihood (ML) detector.

The paper is organized as follows: The section 2 provides the related works on the channel sensing and estimation and proposed ACSCS scheme is presented in Section 3. The simulation results are presented in Section 4 and overall conclusion is presented in Section 5.

2. Related Works

In [15] proposed Statistic spectrum sensing algorithm under complex surroundings in CR networks. The proposed algorithm is based on the Cyclostationary feature detection and theory of Hilbert transformation and this strategy is more flexible i.e. it can reduce the computational complexity, according to the existing electromagnetic surroundings by changing its sampling times and the step size of cyclic frequency. The simulation shows that this scheme can be used to detect both straightforward signals and modulated Cyclostationary signals, and it yields acceptable performance compared to conventional energy detection algorithm. Furthermore, the noise power is unknown for CUs and it provides a satisfactory detection performance, when the SNR is low.

In [16], we have analysed two algorithms such as Adaptive Cross Self-coherent- restoral (ACS) and Cyclic Adaptive Beam forming (CAB) to enhance the sensing performance in medium or weak interference environments. Simulation result shows that the proposed algorithm is more suitable for wireless applications and mobile communications.

In [17] proposed an effective spectrum sensing algorithm for CR to detect PUs as early as possible. The proposed algorithm deals with small data sets to compute real covariance matrix in order to preserve the detection attainment. The simulation shows the comparison between the proposed algorithm and other conventional method using a captured Digital TV (DTV) signal and this proposed method can work either using limited data sets or work under a lower SNR surroundings.

In [18] examined the presentation examination of range detecting of CR under various blurring climate. Range detecting is the really key task of CR. There are different sorts of non-agreeable range detecting strategies which are energy, matched channel and Cyclostationary based identification. Here planning CR frameworks can appraise the energy of the range. By using energy location method, the presentation of the proposed framework is dissected on various blurring channels like AWGN, Rayleigh blurring, and Nakagami blurring channel.

In [19] proposed a FPGA execution of an autocorrelation based range detecting calculations for CR applications. Here, the embellishments of DC offset, recurrence offset and their aggregate presence on range detecting execution are dissected. The remuneration factors, which are incorporated, make the calculation lenient against these two counterbalances. Recreation result done in MATLAB shows the viability of the proposed calculation. Moreover, the proposed calculation is executed on a Xilinx Virtex 5 board (XC5VLX110T) and the equipment results are verified.

In [20] VLSI underlying model for Cyclostationary highlight identification based range detecting for CR framework. Here, VLSI engineering is changed to recognition of calculation for FPGA prototyping and ASIC plan. Framework level plan of this recognition conspire and the models of all its interior blocks have been proposed. Thus, execution examination of the proposed identifier has been dropped in AWGN climate where it could convey 0.95 Location Likelihood at - 6 dB. At long last, the proposed framework level design is orchestrated and post format re-enactments are done.

3. Adaptive Cross Score Cyclostationary 4G Communication

Spectral correlation in the cognitive is effective for the computation of the resource allocation in the wireless communication environment. The proposed Adaptive Cross Score Cyclostationary (ACSCS) model for the resource allocation between the users in the cognitive radio network environment, the autocorrelation function estimation in the stochastic process $g(t)$ is computed as in equation (1)

$$R_g(t,\tau) = E\left[g\left(t+\frac{\tau}{2}\right)g^*\left(t-\frac{\tau}{2}\right)\right] \tag{1}$$

In the above equation (1) the complex conjugation is denoted as *, the sense of Cyclostationary object is denoted as the $g(t)$ with the periodic function of $R_g(t,\tau)$ with the time period of T_0 with time T as computed with Fourier Series measured as in equation (2)

$$R_g(t,\tau) = \sum_\alpha R_g^\alpha(\tau)e^{2\pi\alpha t} \tag{2}$$

Using equation (2) the autocorrelation function is computed periodic manner through the integer multiple of fundamental frequency for the $\frac{1}{T_0}$. The Fourier coefficient of the variables are measured with equation (3)

$$R_g^\alpha(\tau) = lim_{T\to\infty}\int_{-\frac{T}{2}}^{+\frac{T}{2}} R_g(t,\tau)\, e^{-j2\pi\alpha t}dt \tag{3}$$

Where, the integer value is measured as α, the cyclic autocorrelation function (CAF) of the variable is measured with $R_g^\alpha(\tau)$. The cyclic spectrum of the idealized Fourier transform is represented as in equation (4)

$$P_g^\alpha(f) = \int_{-\infty}^{+\infty} R_g^\alpha(\tau)\, e^{-j2\pi f\tau}d\tau \tag{4}$$

With non-probabilistic scheme the time series are measured with $g(t)$ through the second-order periodicity with the synchronized average lag of time-series signal o(t)=g(t+ τ/2)g*(t-τ/2) using the equation (5)

$$\hat{R}_g(\tau,t) \triangleq lim_{M\to\infty}\frac{1}{2N+1}\sum_{n=-M}^{+M} g\left(t+nT_0+\frac{\tau}{2}\right)g^*\left(t+nT_0-\frac{\tau}{2}\right) \tag{5}$$

With equation (5) the periodic autocorrelation between the functions are computed based on the non-probabilistic periodic value of the signal as represented in the equation (6)

$$R_g^\alpha(\tau) \triangleq lim_{M\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{+\frac{T}{2}} g\left(t+\frac{\tau}{2}\right)g^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}dt \tag{6}$$

The spectrum signal autocorrelation function is estimated with the cyclic limits with spectrum function categorized with the Fourier transform as in equation (7)

$$\hat{P}_g^{\alpha}(f) = \int_{-\infty}^{+\infty} R_g^{\alpha}(\tau)\, e^{-j2\pi f\tau} d\tau \tag{7}$$

The proposed ACSCS compute the CAF constructive conjugate function as represented in equation (8)

$$\hat{R}_g^{\alpha}(\tau) = lim_{T\to\infty} \frac{1}{T} \int_{-\frac{T}{2}}^{+\frac{T}{2}} R_g^{*}(t,\tau) e^{-j2\pi\alpha t} dt \tag{8}$$

The ACSCS uses the Cyclostationary feature detection model for the estimation of coherence and synchronization. The estimation is based on the consideration of different signal properties those exhibits the minimal SNR value. Based on consideration of IEEE 802.22 spectrum sensing is adopted with the CR model for the feature detection for the single or multiple frequencies. The feature of the cognitive model is computed based on the oversampling and resolution with the cycle domains and frequencies. The signals are oversample based on the cyclic field with the maximal resolvable cycle satisfies the Nyquist rate frequencies. The spectral resolution of the cognitive user is finer for the cycle frequency of Δα « Δf ≈ (1/T). With the developed frequency and cyclic domain signals with ACSCS is computed for the longer period of time. The SCF function is computed to measure the computational complexity for the specified (α, f), with the SCF value of O(N2 + (N/2) log2N). The energy detector computation complexity is estimated using O((N/2) $\log_2$ N).

3.1 ACSCS Scheme for Cyclostationary Beamforming

The proposed ACSCS scheme uses the algorithm comprises of the SCORE< Least-Square and Cross SCORE. The developed algorithm uses the complex multiplication of O(n3) for the input samples for the antenna array elements. The ALS and ACS algorithm complex multiplication with the complexity value of O(n2). The adaptive Cyclostationary beamforming algorithm computes the desire signal Cochannel interference for the cycle frequency. The cognitive network narrow-band signal are estimated based on antenna array measured with the Signal Of Interest (SOI) g(t),noise and interference, the antenna array signal received is represented as in equation (9)

$$r(t) = sg(t) + i(t) \tag{9}$$

In equation (9), the antenna array SOI factor is represented as s, the interfering signal and channel signal is denoted as $i(t)$. The self-coherent spectrum is denoted as $g(t)$ for the signal α. The Primary user (PU) in the signal form is extracted based on the adaptive beamformer $r(t)$ as in equation (10)

$$O(t) = w^{H} r(t) \tag{10}$$

Where, the $O(t)$ represented as the extracted SOI, the weighted vector with the beamforming is denoted as w^{H} based on interference due to radiation pattern. The overall architecture of proposed ACSCS scheme in 4G communication is presented in figure 1.

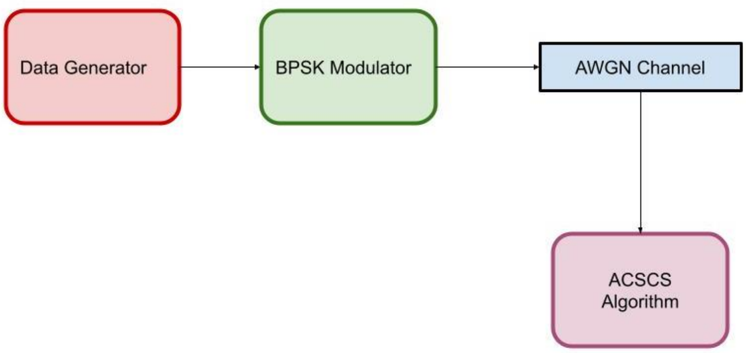


Figure 1. Architecture of ACSCS

The proposed ACSCS uses the adaptive beamforming SCORE for analysis of self-coherence spectral level using the equation (11) with the reference signal s(t)

$$f(t) \triangleq c^H r^{(*)}(t-\tau)e^{-j2\pi\alpha t}(11)$$

The control vector is denoted as c^H for the received signal $f(t)$ for the transmitted signal $g(t)$ in PU signal for the estimation of self-coherence for the frequency separation α. The reference signal decay $f(t)$ for SOI uncorrelated signal value $g(t)$ and $i(t)$ as in equation (12)

$$f(t) = sg(t) + i(t)(12)$$

The ACS estimates the cost function in the cognitive radio network estimated with the function as in equation (13)

$$E_{ALS} \triangleq \langle |o(t) - f(t)|^2 \rangle (13)$$

In above equation (13), the interval time average is denoted as [0, T] and optimized weighted vector is computed.

4. Simulation Results

To observe the performance of the proposed algorithms, few simulations are carried out in this section by considering a uniform linear array with n=4, 8, 12 & 16 elements. The distance between the neighbouring elements is half the wavelength of the carrier frequency 1050 MHz. The spectrum, which is split into five PU channels, is considered as listed in Table 1. In this case, simulations are carried out for 5000 input samples.

Table 1. Spectrum of PU signals

Signals	Carrier frequency (MHz)	Modulation	DOA	SNR	User
P	1051.1	*BPSK*	20^0	16dB	*PU*
Q	1051.1	*BPSK*	*41*	*12*	*PU*
R	1051.1	*BPSK*	*55*	*27*	*PU*
S	1051.1	*BPSK*	*70*	*29*	*PU*
T	1051.1	*BPSK*	*85*	*34*	*PU*

Spectrum sensing algorithms in CR system are analysed for computational complexity reduction using adaptive Cyclostationary beamforming algorithms by considering the signal ‗R‘ as SOI. The computational complexity reduction issues of the ALS, ACS, the proposed ACSCS algorithms and their pipeline implementations for various number of antenna array elements are shown in Table 2. It is observed that, to implement ACS algorithm 466 complex multiplications are required for n=8 and SINR obtained by this algorithm is approximately 5.8 dB. However, ACSCS algorithm provides a better SINR value of 7.1 dB and it requires only 338 complex multiplications to implement ACSCS algorithm for n=8, which is less compared to ACS algorithm. Even though number of complex multiplication required implementing ALS algorithm is around 322 for n=8, it is less compared to ACS and ACSCS algorithms. But it has obtained very low SINR approximately 1.1 dB which is very less compared to other algorithms and it is practically unrealizable

Table 2. Comparison of Computational Complexity

Number of Antenna Array Elements ‘n’	**ALS ($4.75n^2$ +2.25n)**		**ACS ($6.75n^2$ + 4.25n)**		**ACSCS ($4.75n^2$ + 4.25n)**	
	No. of Complex multiplication	**SINR (dB)**	**No. of Complex multiplication**	**SINR (dB)**	**No. of Complex multiplication**	**SINR (dB)**
4	85	0.5	78	1.3	93	5.2
8	322	1.1	189	6.9	338	7.1
12	711	1.6	479	11.4	735	10.3
16	1252	2.3	693	16.8	1284	20.2

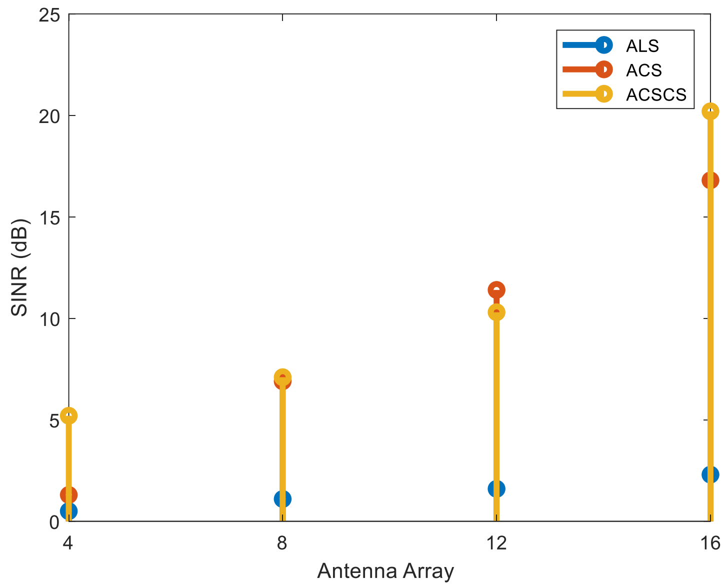


Figure 2. Comparison of Computational Complexity

Moreover, ACSCS algorithm provides a reduced computational complexity approximately 27.4 % compared to ACS algorithm in figure 2. Hence, the ACSCS algorithm rapidly extracts the desired signal from the received signal compared to ACS algorithm. The ALS, ACS and ACSCS algorithm are designed and analysed for their cost function and the results are obtained during simulation as shown in the Table 3. The cost functions is nothing but difference between the output signal $(t)$and the reference signal ft . Based on this erroneous signal, the weighting and control vectors of these algorithms are optimized.

Table 3. Comparison of Cost Function

Spectrum sensing Algorithm	**ALS**	**ACS**	**ACSCS**
Cost Function	0.5409	0.1353	0.0632

From the Table 3, it is also observed that the cost function is approximately reduced to 75% by using the ACS algorithm and 88% by using the proposed ACSCS algorithm compared to ALS algorithm. ROC of Adaptive SCORE and its pipeline implementation of spectrum sensing algorithms by considering signal 'Q' as SOI over Rayleigh fading channel. The probability of detection is presented in table 4.

Table 4. Comparison of Probability of Detection

Probability of False alarm (Pf)	**ALS**	**Pipeline implementation Of ALS**	**ACS**	**Pipeline implementation Of ACS**	**ACSCS**	**Pipeline implementation Of ACSCS**
	Detection Probability ($Pdet$)	Detection Probability ($Pdet$)	Detection Probability ($Pdet$)	Detection Probability ($Pdet$)	Detection Probability ($Pdet$)	Detection Probability ($Pdet$)
0.2	0.01	0.01	0.01	0.03	0.78	0.8
0.4	0.08	0.07	0.08	0.08	0.9	1
0.6	0.4	0.5	0.3	0.5	1	1
0.8	0.8	0.7	0.7	0.7	1	1
1.0	1	1	1	1	1	1

The figure 4 and figure 5 provides the detection probability value of the ALS, ACS and ACSCS scheme based on false alarm probability value.

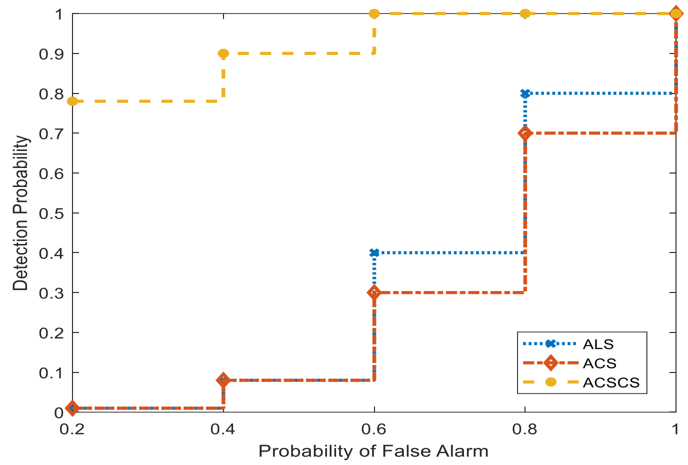


Figure 4. Comparison of Detection Probability

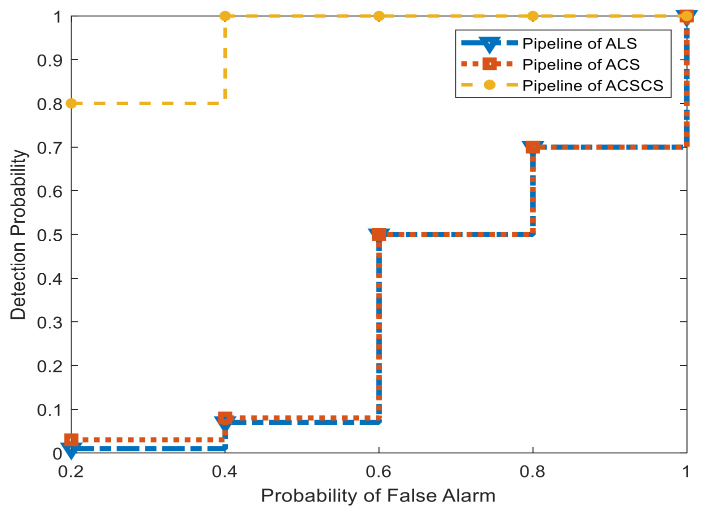


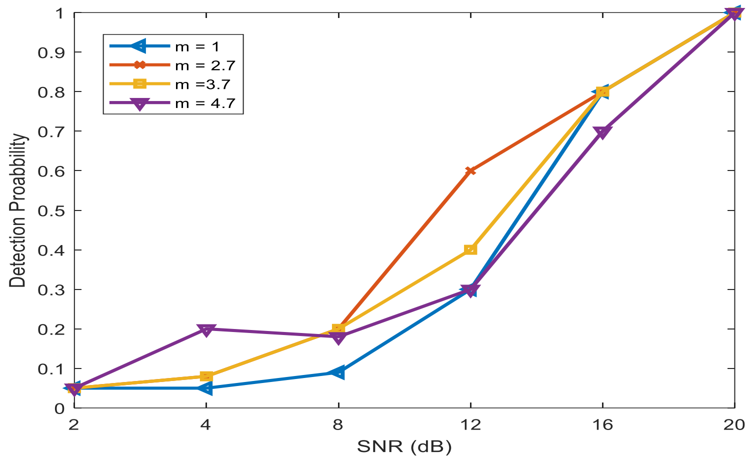
Figure 5. Comparison of Detection Probability in Pipeline Model

From the Table.5, it is observed that, when the probability of false alarm $Pfalse$ is 0.4, the Detection Probability$Pdet$ is approximately 0.45 by using ALS algorithm whereas the pipeline implementation of ACSCS provides better $Pdet$ value of 0.9 compared to other algorithms. It is also seen that the value of Detection Probability$Pdet$ increases while the original ALS, ACS and ACSCS algorithms are implemented in pipeline over Rayleigh fading channel.

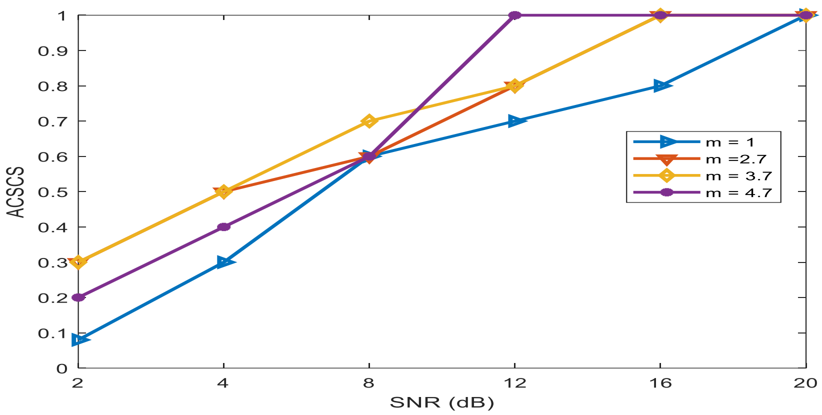
Table 5. Comparison of False Alarm

SNR (dB)	**Pipeline implementation of ALS**				**ACSCS**				**Pipeline implementation of ACSCS algorithm**			
	Detection Probability ($\boldsymbol{Pdet}$)				Detection Probability ($\boldsymbol{Pdet}$)				Detection Probability ($\boldsymbol{Pdet}$)			
	m=1	m=2.7	m=3.7	m=4.7	m=1	m=2.7	m=3.7	m=4.7	m=1	m=2.7	m=3.7	m=4.7
2	0.05	0.05	0.05	0.05	0.08	0.3	0.3	0.2	0.2	0.2	0.2	0.2
4	0.05	0.08	0.08	0.2	0.3	0.5	0.5	0.4	0.3	0.4	0.4	0.4
8	0.09	0.2	0.2	0.18	0.6	0.6	0.7	0.6	0.5	0.5	0.6	0.7
12	0.3	0.6	0.4	0.3	0.7	0.8	0.8	1	0.7	0.7	0.8	1
16	0.8	0.8	0.8	0.7	0.8	1	1	1	0.9	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1

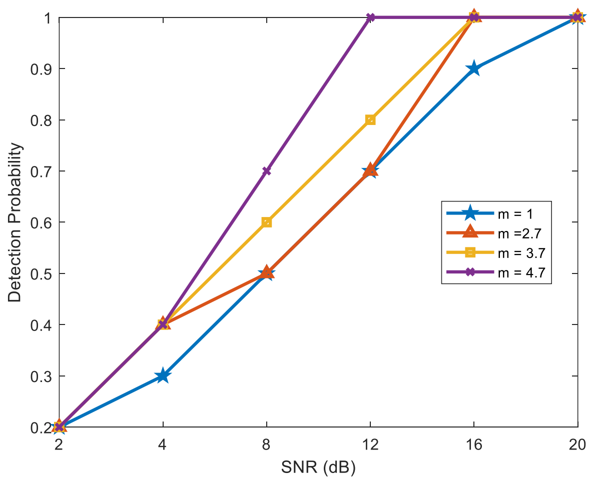
The figure 6(a), 6(b) and 6(c) illustrated the probability of detection for the comparative examination of false alarm with the ACSCS scheme for the spectrum sensing and resource allocation.



(a)



(b)



(c)

Figure 6. Comparison of Detection Probability (a) ALS (b) ACS and (c) Pipeline ACSCS

Table 5 represents the Detection Probability $Pdet$ which is computed for different values of SNR by using the proposed ACSCS algorithm and the pipeline implementations of ALS, ACS and ACSCS algorithms over Nakagamim fading channels. By considering the four isotropic arrays, the proposed algorithms are simulated for various values of Nakagami parameter m=1, 2.7, 3.7, and 4.7. Here, both the integer and non-integer values of Nakagami-m parameter are considered. Rayleigh value matches with the Nakagami, when m= 1. It is also observed that, for SNR = 8dB and m=3.7 combinations, $Pdet$ by ACSCS algorithm is approximately 0.5 whereas pipeline implementation of ACSCS algorithm provides better $Pdet$ value of 0.69 compared to other algorithms. With the Nakagami fading model the developed ACSCS scheme exhibits higher fading index value of m with the improved performance. The increased fading index exhibits the higher average SNR value for the degraded received signal value with the improved probability of detection.

5. Conclusion

For the optimization of weighting vector, it is observed that by using the proposed ACSCS algorithm the Cyclostationarity-based sensing in CR system provides better computational complexity reduction approximately 27.4 % compared to ACS algorithm. Further, approximately 90% reduction is achieved, when this proposed algorithm is implemented in pipeline. It is also observed that the cost function is approximately reduced to 75% by using the ACS algorithm and 88% by using the proposed ACSCS algorithm compared to ALS algorithm. When these algorithms are implemented in pipeline, the cost function is further reduced to 29% and 75% compared to original ACS and ACSCS algorithms, respectively. It is also noted that the pipeline implementation of ACSCS algorithm provides better reduction in device utilization approximately 47 % compared to original ALS, ACS and ACSCS algorithms, when it is realized in FPGA. Thus, the proposed pipeline implementation of ACSCS algorithm shows superior performance to all other algorithms.

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